Perceptions of AI-Edited Video News: Evaluation, Classification, and Attitudes

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***Abstract*—With video news gaining more and more popularity, Artificial Intelligence (AI) video editing tools could be implemented to accelerate video news production. A challenging issue, however, is the quality of AI-edited video news and the acceptance of such news by media consumers. A cross-sectional survey with 2,219 participants across three independent waves was conducted in Germany to assess audience perceptions of video news clips edited by AI-based systems and by professional human editors. All survey participants were recruited by a commercial survey company. Participants were generally unable to reliably identify whether video clips were edited by humans or AI systems. Across several quality dimensions, ratings of AI-edited and human-edited clips were descriptively similar, with overlapping confidence intervals on multiple indicators. Future research can benefit from investigating fatigue related to AI tools and testing algorithmic performance improvements.**

Keywords-Artificial Intelligence; AI; video editing; video news; algorithms; AI evaluation.

I. INTRODUCTION

Expanding upon the presented survey results of a preliminary survey testing Artificial Intelligence (AI) video news editing algorithms in [1], this paper highlights the changes in survey design based on previous results, presents more detailed results from the first survey wave and includes additional survey waves conducted since the publication of the first conference paper at AIMEDIA 2025.

Video news has been established as a strong contender for attention in the digital landscape, aided by the rise of TikTok and their short form video content that is making a jump to other social media platforms [2]. This creates a need for quick video news reporting, a need that could be aided by implementing AI editing tools.

With 40% of young people preferring social media search engines over traditional means [2], the market share of video news reporting on social platforms will continue to grow. This is aided by media publishers who put a bigger focus on digital video production [2] making it clear that the video news reporting demand will increase, and the market is preparing to supply by offering more and more AI tools. One example for this is the launch of the AI writing tool “ChatGPT” in 2022, establishing AI tools as more and more popular and expected to reach a global market share of “more than 2.5 trillion USD by 2032” [3]. Creative industries have implemented generative AI and AI algorithms, for example Adobe Photoshop offering options like generative fill [4], Canva that has its own AI image generation [5] or on countless social media websites via algorithmic AI [6].

The conducted survey consists of three survey waves focussing on different aspects of AI news editing algorithms and their evaluation. Each survey wave consisted of roughly 750 participants split into two groups to investigate whether the tedious process of editing video news clips could be delegated to AI models and how AI editing technology is perceived by humans. In detail, the study measures subjective receptions of video news and survey participants’ evaluation of the quality of editing algorithms as well as attitudes towards AI tools in the media landscape.

This paper details the construction and field deployment of the three survey waves testing two different algorithms [7] against a human and a random edit and presents results on consumer news habits, the performance of the algorithms and attitudes towards the employment of AI in media landscapes, particularly in video news. The focus is put on the survey protocol allowing for statistical analysis of the gathered data. In Section II, the employed algorithms are introduced while Section III introduces the survey protocol by detailing the video experiment and general questions. Additionally, it discusses the details of all three survey waves and a video-based choice experiment questioning the creator of the presented video clips. Section IV presents the results from all survey waves discussing them as well. The presented results, however, are mostly based on bivariate statistics and want to provide an overview on the sample and indicate promising paths for multivariate analysis and statistical models. Section V concludes the compiled research, and Section VI gives a brief outlook in potential future research.

II. EMPLOYED ALGORITHMS

Editing video news clips to employ within the study, comprises of two main steps. In a first step, typically 10 to 15 most suitable scenes for a news story are selected from up to 200 scenes in raw footage. In the second step, the selected scenes are compiled into a video sequence, which is then accompanied by a voice over of a news text to create the final video news clip. The core of the conducted survey waves investigates how automated AI-based editing of video news clips scores against human news editing as a high anchor and a random editing as a low anchor. Hereby, two AI models are considered, which both are described in detail in [7]. The first AI model is the CLIP (Contrastive Language–Image Pre-training) model [8], pairing images of video shots with snippets of news text. The second AI model is denoted as KIGVI (Automatic AI-supported composition of video news clips) model and has been developed by the RheinMain University of Applied Sciences [7]. The KIGVI model was trained using a dataset of 12354 video clips from news segments that ranged from 30 seconds to 5 minutes covering multiple categories of news from the years 2012 to 2025. The second version of the algorithm was further improved by expanding the data set it was being trained on to then compose new news clips that were employed in survey wave 3 [8]. The KIGVI model uses shot detection to split footage into scenes and follows learned professional video editing rules. These rules include varying shot sizes, an initial establishing shot illustrating the main topic and the inclusion of a human-like editing rhythm when composing the video news clip. This marks a major improvement over previous algorithms e.g., the CLIP algorithm that failed to align information sourced in the visual component as well as the textual one. To keep participants engaged, no clip is longer than 35 seconds ensuring that concentration can be maintained throughout the whole survey.

A previous experiment with a small sample size (n = 38 participants) scored the KIGVI algorithm against human edits based on professionality of the edit, choice of scenes and how well the video sequences illustrated the voiceover [7]. The findings of this experiment warranted further investigation with a bigger sample size and a larger survey that asks respondents about their opinion on AI, video news consumption habits and general media reception. Thus, a more comprehensive survey was developed. Human edited news clips were produced by professional editors. In random editing, scenes are randomly selected and compiled into a video news clip. All edited video news clips are voiced over by a professional German recording studio.

III. SURVEY PROTOCOL

A. Basic Principle

The survey is designed as an online survey. The participants of the survey are asked to assess video news clips according to a list of criteria, and to identify the editor of the respective video clip. Field work was done in three waves to allow adaptation of the survey instrument between the waves. The survey waves are designed as three consecutive waves with a similar survey instrument in each wave but different participants. It thus follows a cross-section design and is not a panel study. In general, wave one lead users through questions about news habits, then AI attitudes and AI in news opinions before introducing and conducting the video experiment and closing with sociodemographic factors. Within the video experiment section, users are tasked with attempting to identify the creator of the video clip they were shown. In survey wave 2, the creator identification question was no longer suitable and is therefore eliminated. Survey wave 3 group B excludes the identification question as well.

B. Samples

As a survey area, the greater RheinMain area in Germany is used. The RheinMain area is a multi-state area in southern Germany including major cities like Frankfurt and Wiesbaden, mid-sized cities such as Russelsheim, as well as a number of smaller municipalities. A market research institute was tasked to recruit survey participants living in or around the RheinMain area aged from 16 to 70+ for all survey waves. The frame population thus included participants aged 17 years and older from the online access panel, currently living in the RheinMain area.

C. Survey Structure

In an experiment portion of the questionnaire video news clips are shown, which cover three overall categories of news. These are:

- *Traffic news*
- *Local news*
- *News concerning politics*.

Each of these three categories of news consists of four video news clips, and each video news clip is edited in four different variants, which are:

- *Human editing*
- AI-based editing using the *KIGVI model*
- AI-based editing using the model based on *CLIP*
- *Random editing*.

This results in a pool of 48 video news clips (3 categories × 4 video news clips × 4 variants) in waves 1 and 3 or 36 video news clips (3 categories x 4 video news clips x 3 variants) in wave 2 as shown in Figure 1.

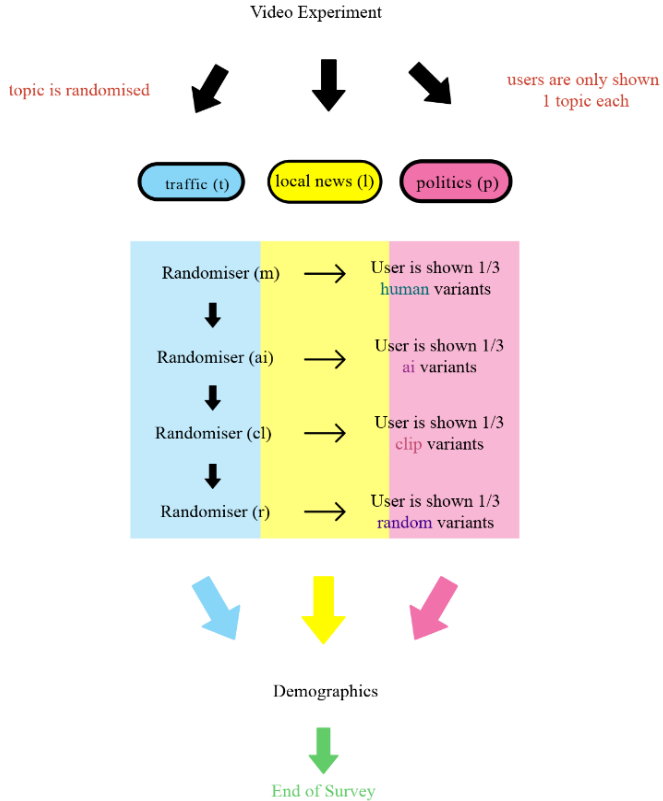

Fig. 1. Survey Protocol outlining randomisation strategy (AI refers to the KIGVI algorithm).

Prior to the experiment portion, the participants received a short introduction before facing a screen-out question that determines whether they agreed to data collection and reside in the greater RheinMain area. Thereafter the participants were asked about their news consumption habits and preferences, how familiar they are with AI in general as well as attitudes towards the technology in general, accounting for both algorithmic and generative AI. The experiment portion was introduced to ensure participants understood the task of evaluating the algorithmic AI technology utilised in the editing process. Matrix questions followed each editing variant in order to assess the quality of a video news clip. A matrix question is the judgement of a specific statement on the Likert-Scale. Eight statements are used in the survey, which are shown in Table I. Response to each question was measured on a six-point Likert-Scale ranging from 1, indicating a strong disagreement to 6 for a strong agreement. An even number of levels was chosen to avoid a neutral position and foster a pro or con decision from the participants.

TABLE I. STATEMENTS BEING JUDGED BY A PARTICIPANT ON A LIKERT-SCALE TO ASSESS THE QUALITY OF A VIDEO NEWS CLIP.

Number	Statement
(1)	The voiceover matches the visual material
(2)	The scenes in the video illustrate all the important information in the program
(3)	The video looks professionally edited
(4)	The video is similar to video news I’ve seen before
(5)	Aspects of the report seem inconsistent / incorrect
(6)	I will probably remember the video report
(7)	The video makes the report more interesting to me
(8)	The report triggers emotion in me

The Likert-scaled items were inherited from a previous quality survey conducted in [8]. Additional questions such as whether participants noticed technical errors like flickering, black screens, timing errors, etc. accompany the inherited questions. Furthermore, the survey instrument included questions evaluating whether the video offered additional value to the news report or evoked emotions. Sociodemographic data, including age, highest level of education and job status were assessed as factors, measured in categories rather than having participants answer freely. For age specifically, category means were used to calculate means and standard deviations, thereby skewing the data. Gender identity was prioritised over gender assigned at birth, however identities beyond male or female were too low in number to be considered.

D. Experimental Design

Responses of the participants to the experiment portion were accompanied by additional Likert-scaled items asking for general attitudes towards news, news reception, artificial intelligence and AI in news. Again, these items were measured on an even scale from *Strongly Disagree* (1) to *Strongly Agree* (6). The experiment portion was randomised. A first randomisation assigned a category of news per participant while a second randomisation within each category selected one video news clip per editing variant meaning every participant was shown one random editing variant, one human editing variant, one AI editing variant using the KIGVI model and one AI editing variant using the model based on CLIP. The video news clips were embedded in the experiment in a way that the participants were able to view them multiple times to secure the responses. Participants were tasked to evaluate the presented video news clip via the matrix questions. Following this evaluation, a choice was presented whether participants believed a human or an AI to be the editor of the before seen video news clip and how confident they were in their choice via Likert scale. Tracking the time, the participants spent on a specific page aimed to make sure that they at least viewed each video news clip once. The first survey wave gathered a general overview of AI evaluation, news habits and algorithmic performance. The second survey wave tested a potential bias towards AI content by flagging the same videos as Human for group A or AI for group B and evaluated perceived differences in algorithmic performance across both groups. The last survey wave received videos edited by an improved algorithm and tested both algorithmic improvements as perceived by audiences as well as influences of removing the AI label from the evaluation process.

E. Survey Waves

The field work was divided into three survey waves. The employment of consecutive waves was chosen arbitrarily to allow adaptations of the survey instrument between the waves. This was necessary to allow the development of the KIGVI-algorithm in reaction to measuring results from a survey wave. Additionally, the chance to adapt the survey instrument within later waves helped focus on specific topics with more or less intensity. In wave 1 sub survey B, the video experiment portion was pulled up in the survey flow to precede the questions about news habit and co. in an effort to potentially rule out effects of fatigue on the data. With survey wave 2 focussing on a potential bias towards AI tools, participants were shown three variants (human, random and KIGVI algorithm) instead of the previous four that still included the CLIP algorithm, and each subgroup received a different introduction. Wave 2 group A received an introduction saying every single video they would be shown was edited via an algorithm despite being shown the three variants. Wave 2 group B received the opposite introduction; they were told all videos were edited by humans. In wave 3, the improved algorithm [9] was employed for both video experiments, wave 3 group A received the same questionnaire as wave 1 group B with the only distinction being the video clips edited via the improved algorithm while wave 3 group B eliminated every mention of AI or algorithmic tools, therefore once again no longer asking participants on whether the watched videos were considered human-edited or AI-edited. All adjustments are detailed in Table II.

TABLE II. SURVEY ADJUSTMENTS PER WAVE.

Wave	Adjustments
1A	Full survey, general questions ahead of video experiment, featuring variants Human, KIGVI (AI), CLIP and Random
1B	Full survey, video experiment ahead of general questions featuring variants Human, KIGVI (AI), CLIP and Random
2A	Shortened survey, shortened Statement matrix only featuring statements 1, 2, 3 and 5 (see Table I), video experiment ahead of general questions with “all videos are edited by AI” introduction featuring variants Human, KIGVI (AI) and Random
2B	Shortened survey, shortened Statement matrix only featuring statements 1, 2, 3 and 5 (see Table I), video experiment ahead of general questions with “all videos are edited by a human” introduction featuring variants Human, KIGVI (AI) and Random
3A	Identical to wave 1B with evolved KIGVI algorithm replacing previous KIGVI clips, featuring variants Human, KIGVI (AI), CLIP and Random
3B	Shortened survey eliminating every mention of AI in both general questions and video experiment, video experiment ahead of general questions, featuring variants Human, KIGVI (AI), CLIP and Random

IV. FIELD WORK AND PARTICIPANTS

Completing the online survey took participants 12 minutes on average. The questionnaires were distributed via online links hosted on the platform Qualtrics. The selection of participants was outsourced to market research company Horizoom. Horizoom distributed the survey links among their registered community, offering points for completing the survey that can culminate in cash earnings as a reward. The Qualtrics survey includes a captcha to ensure human participants only and flags survey responses that it considered to be completed with or by a bot while respondent IDs were generated to ensure privacy and lock previous survey respondents out of completing future survey waves. This guaranteed new recipient pools for every survey wave. Survey wave 1 ran from December 2024 to April 2025, Survey wave 2 ran throughout July 2025 and the final survey wave 3 ran from November 2025 until mid-December 2025. It is important to recognize that the consecutive survey waves employed similar survey instruments but different survey participants. The survey design is thus cross-sectional and not a panel. The sample sizes of validly completed questionnaires were 794 (wave 1), 722 (wave 2) and 703 (wave 3), resulting in a slightly higher sample size than the aimed for of 750 for the first wave and slightly lower sample sizes for waves 2 and 3 when it came to 100% completion. Within each wave, both sub-surveys had a mostly equal valid sample size.

A. Wave 1

In the sample of 794 individuals, 57.63% of survey participants reported identifying as female. The mean age of participants in Wave 1 was 41.69 (*SD* = 21.75). 45.80% of participants reported having finished their A-levels, 23.79% had one or multiple university degrees and 5.60% completed any vocational training. For job placements, 61.53% of participants reported currently being employed, 11.21% reported being unemployed, 10.57% chose pensioneer as an option while 8.79% considered themselves self-employed.

B. Wave 2

In the sample of 722 individuals, 58.24% of survey participants reported identifying as female. The mean age of participants in Wave 2 was 44.48 (*SD* = 20.42). 41.35% of participants reported having finished their A-levels, 16.76% had one or multiple university degrees and 7.14% completed any vocational training. For job placements, 62.36% of participants reported currently being employed, 5.49% reported being unemployed, 4.26% chose pensioneer as an option while 7.14% considered themselves self-employed.

C. Wave 3

In the sample of 703 individuals, 56.53% of survey participants reported identifying as female. The mean age of participants in Wave 1 was 45.88 (*SD* = 21.68). 51.14% of participants reported having finished their A-levels, 22.22% had one or multiple university degrees and 6.41% completed any vocational training. For job placements, 64.18% of participants reported currently being employed, 8.40% reported being unemployed, 12.96% chose pensioneer as an option while 7.55% considered themselves self-employed.

D. Comparison Between Respondents per Wave

Table III provides an overview on selected socio-demographic characteristics of the respondents´ per survey wave. Although some differences can be identified, a chi-square tests and Kolmogorov–Smirnov tests indicate no statistically significant differences in age and gender distributions across the three survey waves. However, significant differences were observed in education levels between waves ($\chi^2 = 137$; $p < 0.001$). This variation is therefore considered a potential confounding factor in the analytical strategy.

TABLE III. GENDER, AGE & EDUCATION PER WAVE

	Wave 1 *N* = 794	**Wave 2** *N* = 722	**Wave 3** *N* = 703
Gender			
Female	58.23%	58.24%	56.61%
Male	40.23%	41.62%	42.96%
Diverse	1.54%	0.14%	0.43%
Age (mean)	41.69	44.48	45.88
Education Level			
Entry	23.16%	16.62%	18.66%
Medium	69.59%	58.17%	73.36%
High	7.25%	25.21%	7.98%

The particular relevance of the influence of education on media use and media literacy has been empirically proven many times internationally (see, for example [9]). Numerous studies show that formal education is systematically linked to usage patterns, media literacy, and the ability to critically evaluate media content. Against this background, a comparable distribution of educational levels between samples is central to the interpretation of differences in media use. Since the second wave of the survey differs significantly from the other two waves in terms of the distribution of the educational characteristic, direct comparisons can only be interpreted to a limited extent. To avoid distortions due to structural sample differences and to ensure the comparability of the results, the second wave is not considered in the following analysis. The results of the study therefore refer exclusively to the first and third waves of the survey, which are much more consistent in terms of educational structure. In the following we present three sections with different analyses that build upon each other to illustrate influences on the video experiment with more detail.

V. ANALYSIS OF MEDIA USAGE BEHAVIOUR

A. Patterns of Media Consumption

The study revealed differences in the respondents' perception of public versus private media offerings. An overview of the distribution is presented in Table IV. A chi-square test indicates a significant connection between the survey wave and the usage behaviour reported by the respondents ($\chi^2 = 7.08$; $p < 0.05$). Since this effect could be attributed to both a possible time effect and differences in the composition of the respective samples, the decision to use exclusively public or exclusively private media offerings was examined separately in a future analysis step, which is beyond the scope of the present paper, employing binary logistic regression. Specifically, the analysis showed that there is no clear effect of the survey wave or the survey date on the stated choice between public and private media offerings once the level of education is controlled for. In line with the existing literature, however, both models revealed a significant influence of the education characteristic on this decision, confirming the fundamental relevance of education-related differences in media use (Public News: $\chi^2 = 11.21$; $p < 0.01$; Private News: $\chi^2 = 11.47$; $p < 0.01$). In addition, a clear differentiation between user groups emerged: people with a lower level of education significantly more often prefer private media offerings than people with a medium level of education, while the opposite pattern can be observed for public media offerings. For people with a high level of education, however, no clear correlation can be established on the basis of the available analyses. Interestingly, there was no significant temporal effect on the stated choice of public media offerings, while a significant relationship with the time of the survey or the survey wave was observed for private media offerings ($\chi^2 = 5.88$; $p < 0.05$).

TABLE IV. PREFERANCE TOWARDS PUBLIC OR PRIVATE NEWS AMONGST PARTICIPANTS IN ALL THREE SURVEY WAVES.

	Public News	Private News	Public and Private News
Wave 1	42.69%	12.96%	44.35%
Wave 3	46.76%	8.68%	44.56%

In addition, the influence of gender and age on voting decisions was examined. Age was found to have a fundamental effect on media choice (Public News: $\chi^2 = 9.66$; $p < 0.01$; Private News: $\chi^2 = 11.45$; $p < 0.01$), but this effect varied depending on the type of media offered: while public media offerings were more frequently chosen by younger people, the results indicate that older people tend to use private media offerings. However, a weak significant gender-specific difference was only found in the choice of private media offerings, with a larger proportion of women than men opting for private media offerings ($\chi^2 = 4.09$; $p < 0.1$). Participants were asked to indicate which platforms they use for news consumption, ranging from digital-only sources (news websites, social media, and apps) to more established platforms (television and radio). Most respondents reported using multiple platforms, while substantial subgroups relied exclusively on social media or exclusively on television for news consumption. These patterns were consistent across both survey waves. Regarding video news consumption, an average of 45% of participants reported watching video news daily, while approximately 30% indicated consumption at least once per week. Across waves, women reported daily video news use more frequently than men but also showed higher proportions of very infrequent use (less than once per month). This pattern was observed again in wave 3, although the proportion of men reporting very infrequent use increased. Age-related differences were pronounced: a large share of participants aged 61 years and older reported never watching video news, whereas younger age groups predominantly reported daily or monthly use. Differences by education were less pronounced, though participants with lower educational attainment more frequently reported weekly or monthly use, while those with medium and higher education levels more often reported daily consumption. When asked about satisfaction with the available news content, women more frequently reported being satisfied or mostly satisfied compared to men. By age group, participants aged 41 years and older expressed the highest levels of dissatisfaction, while those aged 31–40 reported the highest satisfaction. In terms of education, respondents with lower and medium educational attainment were less satisfied with the current news offering, whereas those with higher education levels reported greater satisfaction. Regarding familiarity with generative AI, 47% of participants reported having used or currently using AI tools, and approximately 16% indicated that they consume AI-generated content. Around 30% stated that they had no direct contact with AI tools. In light of the general difficulty participants showed in identifying AI-generated or AI-assisted content, this self-reported lack of exposure should be interpreted cautiously, as it may reflect limited awareness rather than actual absence of contact with AI systems.

B. Attitudes towards AI

Attitudes toward the implementation of AI in the media landscape were largely consistent across waves, showing an overall tendency toward critical evaluations (see Table V). However, this result should be interpreted cautiously, as the item was only included in wave 3A and therefore based on a smaller subsample than in previous waves. A chi-square test indicated a significant but weak association between survey wave and response pattern ($\chi^2 = 7.36$, $p < .10$), which may be attributable to differences in the educational composition of the samples. Across waves, respondents more frequently selected the moderate response categories ("rather positive" and "rather negative") than the more extreme positions. While wave 1 included both the highest proportion of clearly negative evaluations and the highest proportion of rather positive attitudes, respondents in wave 3 expressed a generally more critical stance toward the use of AI in media.

TABLE V. EVALUATION OF AI USAGE IN MEDIA CONTEXTS BY PARTICIPANTS IN SURVEY WAVES 1 AND 3.

	Positive	Rather Positive	Rather Negative	Negative
Wave 1	14.27%	34.37%	33.85%	17.51%
Wave 3	10.09%	33.83%	40.95%	15.13%

To gain a better understanding of the underlying mechanisms, the same question was subsequently analysed separately for male and female participants, revealing a stronger differentiation across all three waves (see Table VI). A weak association between gender identity and attitudes toward AI was observed in the analysis of variance (ANOVA; Type I sum of squares = 2.34, $p < .10$; Type III sum of squares = 2.43, $p < .10$). Given the small effect size and the marginal level of statistical significance, these results should be interpreted with caution. Descriptively, male participants in wave 1A expressed slightly more positive attitudes toward AI, whereas female participants tended to evaluate AI more critically. In wave 1B, both genders evaluated AI somewhat more negatively, although the differences were minimal. In wave 3, negative evaluations increased across both gender groups, suggesting a general shift in attitudes rather than a gender-specific effect.

TABLE VI. EVALUATION OF AI USAGE IN MEDIA CONTEXTS BY PARTICIPANTS DIVIDED BY GENDER AND SUB-WAVE.

Attitude towards AI	Gender	
	Female	Male
Wave 1A		
Positive	6.79%	6.53%
Rather Positive	19.58%	13.05%
Rather Negative	21.15%	12.27%
Negative	8.88%	6.53%
Wave 1B		
Positive	7.33%	6.54%
Rather Positive	20.16%	12.83%
Rather Negative	20.42%	10.47%
Negative	8.64%	9.16%
Wave 3A		
Positive	4.02%	5.75%
Rather Positive	17.82%	14.37%
Rather Negative	23.85%	15.52%
Negative	8.33%	5.75%

Attitudes toward AI were additionally examined by education level (see Table VII). For analytical clarity, education was grouped into three categories: low (below A-levels), medium (A-levels, vocational training, or university degree), and high (completed PhD). As with the gender analysis, these results are interpreted descriptively, as the uneven distribution of education levels across waves limits the strength of causal inferences. A significant association between education level and attitudes toward AI was identified using analysis of variance (ANOVA; Type I sum of squares = 4.69, $p < .10$; Type III sum of squares = 5.81, $p < .05$). Given the modest effect sizes and the variation in sample composition across waves, these results should be interpreted cautiously. Descriptively, participants with lower educational attainment evaluated the use of AI in media more critically in wave 1A, whereas participants with medium education levels were more evenly divided and those with higher education tended toward more critical evaluations. In wave 1B, lower and higher education groups expressed slightly more positive attitudes, while the medium education group showed a more negative tendency. In wave 3, attitudes toward AI became more critical overall, particularly among participants with low and medium education levels, while attitudes among the highly educated changed only marginally.

TABLE VII. EVALUATION OF AI USAGE IN MEDIA CONTEXTS BY PARTICIPANTS DIVIDED BY EDUCATION LEVEL AND SUB-WAVE.

Attitude towards AI	Education Level		
	Entry	*Medium*	*High*
Wave 1A			
Positive	3.09%	9.26%	0.95%
Rather Positive	6.89%	22.80%	2.85%
Rather Negative	9.26%	22.80%	1.19%
Negative	4.51%	9.26%	2.14%
Wave 1B			
Positive	5.67%	7.22%	1.03%
Rather Positive	7.99%	22.68%	2.32%
Rather Negative	6.70%	22.68%	1.80%
Negative	5.15%	11.34%	1.03%
Wave 3A			
Positive	0.85%	7.37%	1.42%
Rather Positive	5.67%	24.08%	2.55%
Rather Negative	7.93%	28.33%	2.83%
Negative	3.40%	9.63%	1.42%

In addition to education, attitudes toward AI in media were also examined across age groups (see Table VIII). A significant association between age group and attitudes toward AI was identified using analysis of variance (ANOVA; Type I sum of squares = 25.55, $p < .001$; Type III sum of squares = 26.14, $p < .001$). Across waves, participants aged 61 years and older consistently expressed more negative attitudes toward AI use, whereas participants aged 16–30 tended to evaluate AI more positively, with the exception of wave 3A, in which this pattern was reversed. Participants aged 31–60 generally followed the overall wave-specific trend, expressing more positive attitudes in waves 1A and 1B and slightly more negative attitudes in wave 3A. Although these patterns are robust in terms of statistical significance, they should be interpreted cautiously given the cross-sectional design of the study.

TABLE VIII. EVALUATION OF AI USAGE IN MEDIA CONTEXTS BY PARTICIPANTS DIVIDED BY AGE GROUP AND SUB-WAVE.

Attitude towards AI	Age Group		
	16-30	*31-60*	*61+*
Wave 1A			
Positive	4.77%	8.54%	0.25%
Rather Positive	10.30%	18.34%	3.52%
Rather Negative	7.79%	16.58%	8.79%
Negative	5.53%	6.78%	3.77%
Wave 1B			
Positive	6.46%	6.72%	0.52%
Rather Positive	13.95%	17.05%	2.07%
Rather Negative	9.04%	16.28%	5.94%
Negative	3.36%	9.82%	4.39%
Wave 3A			
Positive	1.14%	7.14%	1.43%
Rather Positive	7.71%	19.43%	5.14%
Rather Negative	8.57%	18.29%	12.29%
Negative	3.43%	9.14%	1.71%

In addition, participants were asked to assess how they perceived attitudes toward AI within their immediate social environment. The prevailing perception was that others held rather positive views of AI technologies, although a notable proportion of respondents indicated uncertainty. Only a small minority assumed that their social surroundings held predominantly negative opinions of AI. Self-reported AI usage patterns largely mirrored attitudinal differences. Across all waves, women reported slightly higher usage of AI tools than men, while consumption of AI-generated content was more evenly distributed across genders. Age-related differences in usage aligned with attitudes: participants in the youngest (16–30) and middle (31–60) age groups reported the highest levels of AI use, whereas those aged 61+ most frequently reported neither using AI tools nor consuming AI-generated content. Differences were also evident across education levels, with participants holding higher educational qualifications more frequently reporting AI usage or consumption, while those with lower educational attainment more often reported no direct contact with AI. Medium education levels likewise showed comparatively high levels of AI usage.

C. Experiences in Video Editing and AI-use in Media

Participants who reported having some or extensive knowledge of video editing were asked to identify potential advantages and disadvantages of using AI tools in media production. The most frequently mentioned advantages included time savings, opportunities for innovation and idea generation, cost reduction, and easier access to media production for novices. Commonly cited disadvantages were the potential replacement of human workers by AI technologies, risks related to copyright infringement, and the reproduction or amplification of biases in AI systems trained on biased data. In addition, participants with a background in video editing were asked to evaluate a set of statements regarding the integration of AI in media production, as presented in Table IX.

TABLE IX. STATEMENTS BEING JUDGED BY A PARTICIPANT ON A LIKERT-SCALE TO ASSESS WISHES TOWARDS THE INTEGRATION OF AI IN MEDIA LANDSCAPES.

Number	Statement
(1)	I want more AI in media landscapes
(2)	I want content that involves AI to be clearly flagged in media landscapes
(3)	I want less/no AI in media landscapes
(4)	I perceive AI in media landscapes as problematic
(5)	I worry that news that were produced with the help of AI tools are not verified upon their factual correctness by a team of human experts

Agreement or Disagreement including standard deviation are pictured in Figure 2. Statement 1 received comparatively low agreement on the Likert scale, indicating a perceived saturation of media landscapes and a general preference for maintaining or reducing the current level of AI use. In contrast, strong agreement was observed for Statement 2, reflecting a clear demand for transparent labelling of AI-generated or AI-assisted content. Statements 3 and 4 were rated on the agreeing side of the scale, suggesting that participants perceive the increasing use of AI in media as potentially problematic or disruptive. Notable agreement was also found for concerns about the absence of human expert oversight in verifying the factual accuracy of news content produced or supported by AI systems.

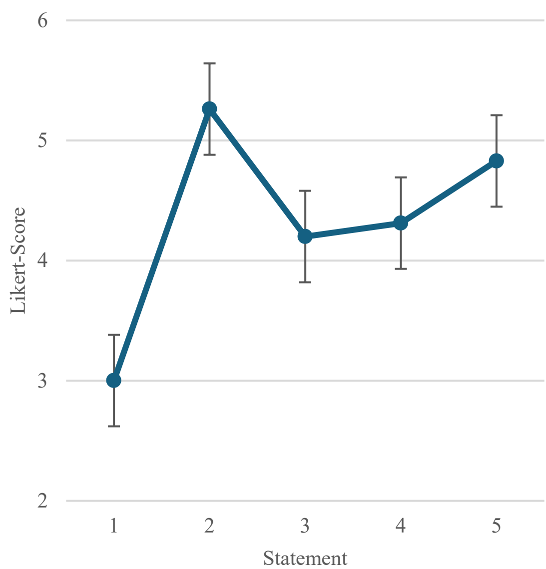

Fig 2. Average scores on the Likert-Scale versus judged statement of Table IX (n = 922 respondents).

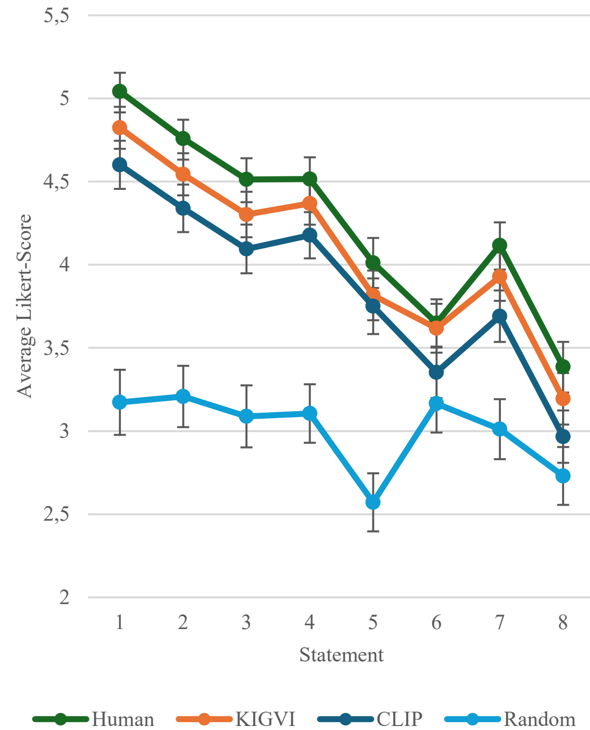

Fig 3. Average scores on the Likert-Scale in wave 1 versus judged statement of Table 1.

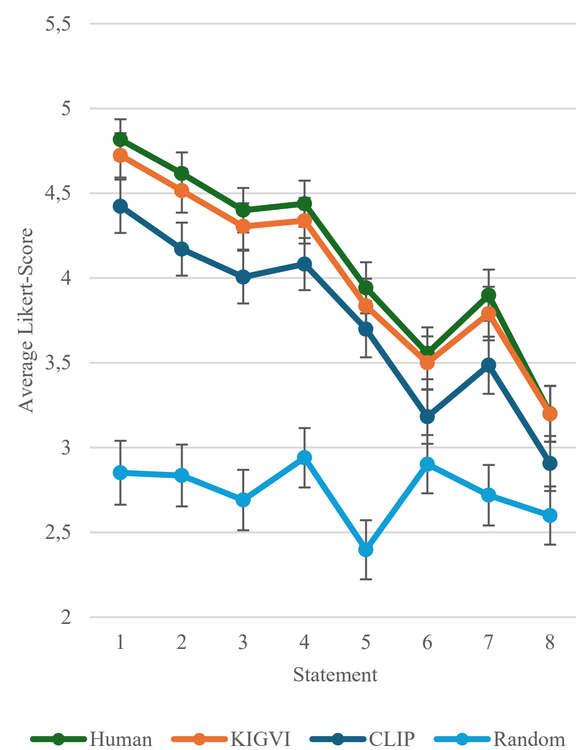

Fig. 4. Average scores on the Likert-Scale in wave 3 versus judged statement of Table 1.

D. Video Experiment

The video experiment assessed participants' agreement with the statements shown in Table I, separately for each editing variant. Evaluations were conducted across three independent survey waves and are displayed with 95% confidence intervals in Figure 3 showing results for wave 1 and Figure 4 showing results for wave 3. The confidence intervals are presented for descriptive purposes only and are not interpreted as evidence of statistical equivalence or difference between variants. Statement 5 was recoded to ensure consistent graphical interpretation; accordingly, lower values on this item indicate a higher number of perceived inconsistencies or errors. Across all waves, the random edit (low anchor) consistently received the lowest ratings across all eight statements, indicating that participants were able to discriminate between clearly divergent quality levels. The CLIP-based edits were evaluated less favourably than both the human edits and the KIGVI-based edits on all statements. This suggests that CLIP-based edits may approximate familiar stylistic conventions without achieving higher perceived quality on other dimensions. Across all variants, a downward trend was observed for memorability (statement 6) and emotional engagement (statement 8). Based on this pattern and to reduce respondent burden, statements 4, 6, 7, and 8 were omitted in wave 2. This decision was made after wave 1 had produced stable results for these items and after the experimental block was moved to the beginning of the questionnaire to minimise fatigue effects. For the same reason, the CLIP condition was also excluded in wave 2. All omitted statements were reintroduced in wave 3 to allow renewed assessment under comparable conditions, as shown in Figure 4. The results for wave 3, presented in Figure 4, largely replicate the patterns observed in Figure 3. The random edit again received the lowest evaluations, while the human and KIGVI edits were rated more favourably across most dimensions. Although higher mean ratings for KIGVI-based edits compared to CLIP-based edits are observed in wave 3, these differences are interpreted descriptively only and do not constitute evidence of algorithmic improvement at this point. Future work will address longitudinal analysis and causal performance comparisons. Across waves, the human edit and the KIGVI edit showed similar evaluation patterns on several indicators, including perceived professionality (statement 3), similarity to existing video news (statement 4), memorability (statement 6), interest generation (statement 7), and emotionality (statement 8), with overlapping confidence intervals. Both variants were also associated with the lowest levels of perceived technical errors or inconsistencies. In addition, participants reported high agreement that the voiceover matched the visual content and that scene selection adequately represented the narrated information. These results indicate perceptual convergence between human-edited and AI-edited variants on multiple quality dimensions.

Another focus of the analysis was the comparison of audience evaluations of CLIP- and KIGVI-edited clips. In wave 1, KIGVI-edited clips received higher average ratings than CLIP-edited clips across all measured dimensions as pictured in Figure 5 and Figure 6.

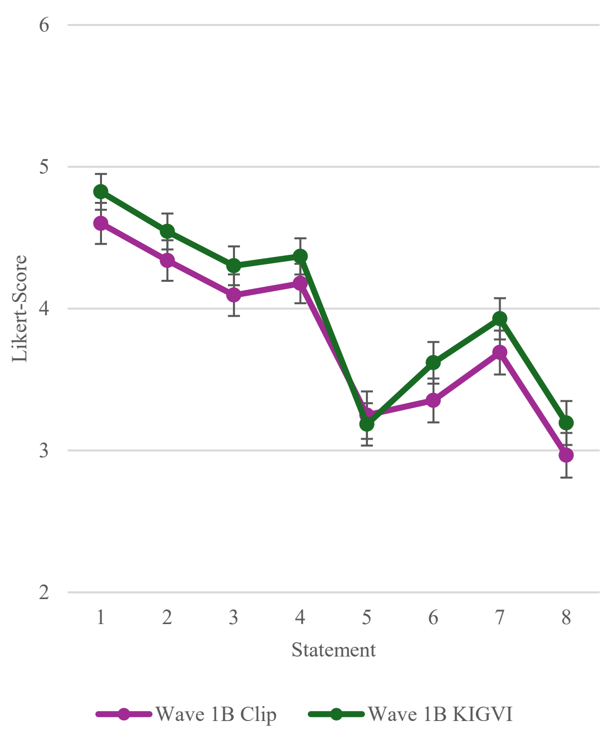

Fig. 5. Average scores on the Likert-Scale of the KIGVI and the CLIP algorithm in wave 1 versus judged statement of Table I.

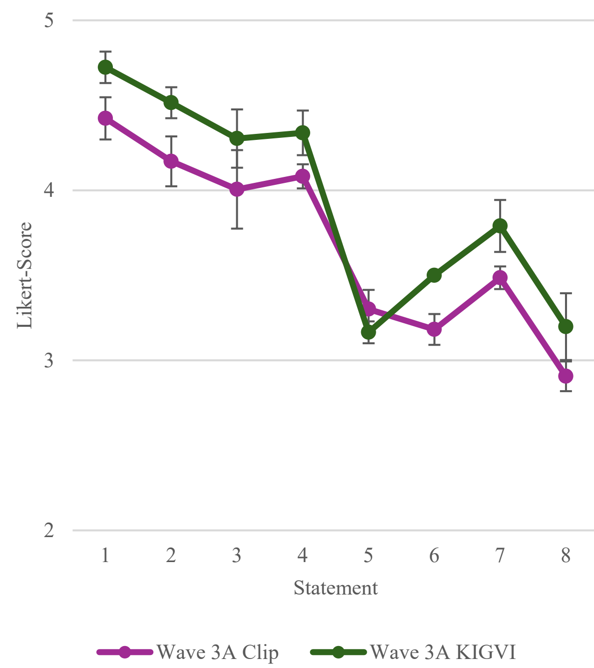

Fig. 6. Average scores on the Likert-Scale of the KIGVI and the CLIP algorithm in wave 3 versus judged statement of Table 1.

These Figures are a closer look at just the two employed algorithms as featured in Figures 3 and 4 above already to allow for a closer identification of performance evaluation across the matrix. While the KIGVI algorithm in version 1 already performs better than the CLIP algorithm across all measures, these margins widen for iteration 2 in wave 3 once more. The results in wave 3 widen especially for statement 4 detailing a high comparability level with existing video news. Memorability (6) scores lower in wave 3 than 1 but still shows a larger margin between the two algorithms. Interest in the topic due to the video edit (7) has the KIGVI algorithm score much higher too and emotionality (8) shows by far the widest gap in evaluation in wave 3 where wave 1 had the algorithm evaluation much closer.

While comparing the evaluation of the performance of the KIGVI algorithm in wave 1 versus wave 3 does not actually produce a significant improvement, looking at the CLIP algorithm evaluation and the random evaluation paints a different picture. Since only the KIGVI algorithm was changed for wave 3 but every other component stayed constant, the other variants can be read as an anchor value too with the significantly lower evaluation of the CLIP algorithm and the random edit whereas the KIGVI algorithm received the same scores in wave 1. However, these differences are reported descriptively and cannot be interpreted as clear statistical evidence of algorithmic improvement due to the cross-sectional design. The identification of the creator of the clips was another consideration within waves 1A, 1B and 3A. In wave 1A, 45.02% of users considered the KIGVI algorithm to be human edited and only 35.32% identified it as AI edited.

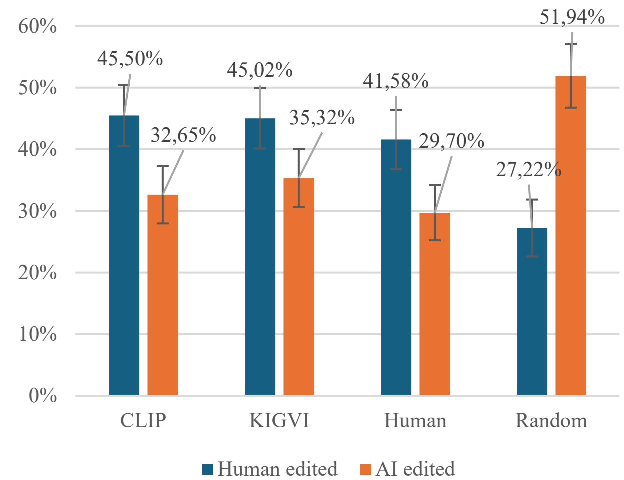

Fig. 7. Percentage of survey participants voting "human creator" (blue), "AI creator" (orange) in wave 1A.

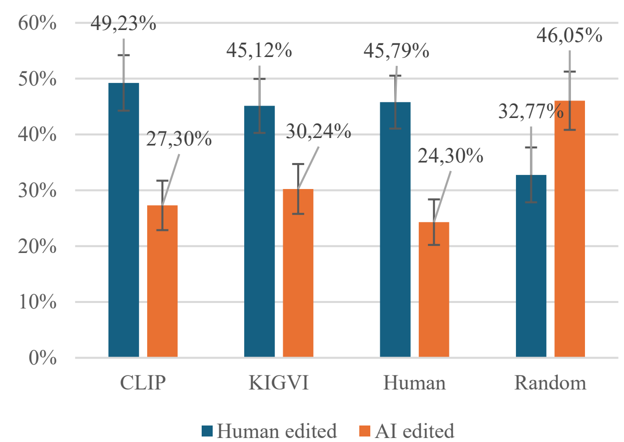

Fig. 8. Percentage of survey participants voting "human creator" (blue), "AI creator" (orange) in wave 2B.

A similar number of participants considered the CLIP algorithm as human edited as well while 29.70% considered the human edit to be done by AI. The random edit was labelled as AI by 51.94% of users. These percentages are shown in Figure 7. In wave 1B, these numbers change slightly as shown in Figure 8. Here, the CLIP algorithm is considered human by 49.23% and the KIGVI algorithm by 45.12%. The random edit is still mostly considered as AI edited despite numbers sinking. The human edit is identified as human more confidently as well.

In wave 3, the random edit was more frequently classified as AI-edited than in wave 1, with nearly 60% of participants selecting AI as its creator. At the same time, confidence in identifying the human-edited clips decreased, while KIGVI-edited clips were more often classified as both human-edited and AI-edited than in earlier waves. Overall, the proportion of participants classifying KIGVI-edited clips as human-edited increased in wave 3. CLIP-edited clips continued to receive

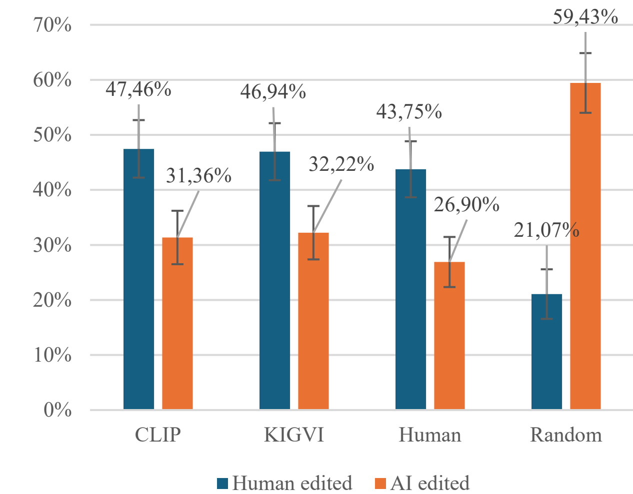

Fig. 9. Percentage of survey participants voting "human creator" (blue), "AI creator" (orange) in wave 3A.

the highest proportion of human-edited classifications, although this proportion was lower than in wave 1B. Additionally, voting behaviour was tested against gender identity excluding options other than male or female due to the small number of responses. This focus was chosen over a testing of educational levels or age since differences were significant within the gender testing. The results for wave 1A are shown in Figure 10. Since Figure 10 does not account for the actual creator of the video, it merely offers insight into voting behaviour by gender displaying a disparity between men and women voting AI as the creator of the clip they were shown with men voting for AI less often and women voting for human slightly more often. The same testing was applied to wave 1B and wave 3A as shown in Figures 11 and Figure 12. In wave 1B, women were even more likely to vote human than men were while in wave 3B, the percentage of women voting for AI climbs higher than in both previous sub-waves. Male participants show a trend towards voting AI as the creator less across all three sub-waves.

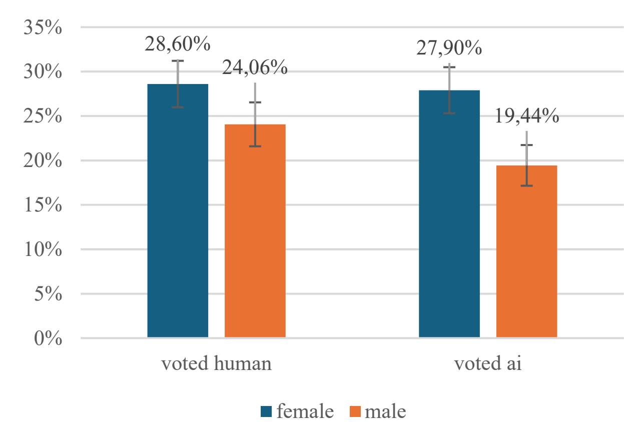

Fig. 10. Percentage of survey participants voting "human creator" (blue), "AI creator" (orange) by gender in wave 1A.

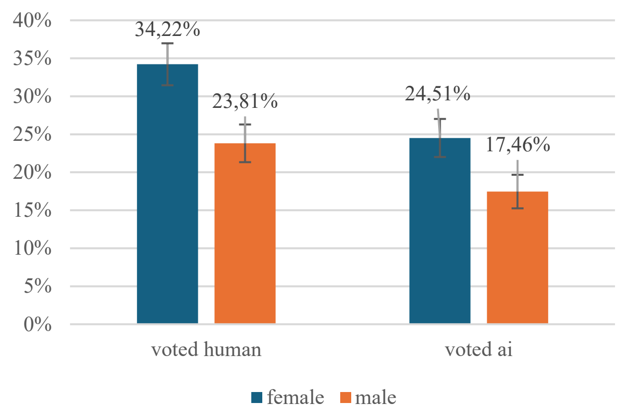

Fig. 11. Percentage of survey participants voting "human creator" (blue), "AI creator" (orange) by gender in wave 1B.

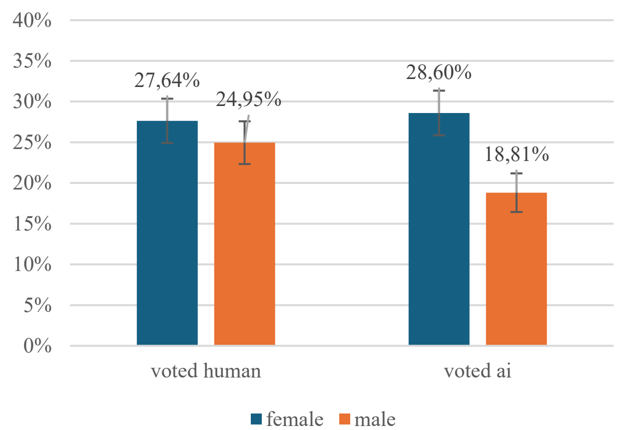

Fig. 12. Percentage of survey participants voting "human creator" (blue), "AI creator" (orange) by gender in wave 3A.

However, the AI selection distinction across gender is significant in all three sub-waves while the human selection is only significant in wave 1B. When users were asked to select whether they paid more attention to the video and its edit or the content of the video, the majority of users (51.07% in wave 1, 49.58% in wave 3) answered in favour of the video content. The question was cut in wave 2.

V. DISCUSSION

A. Patterns of Media Consumption

The observed differences in media choice by age and gender can be plausibly classified in light of existing research on digital inequalities and media preferences. The opposite age effect – with younger people making greater use of public media offerings and older people preferring private offerings – is consistent with findings that media use is not only generation-specific but also influenced by different media socialization and routines (cf. [11]; [12]) The significant gender-specific difference in the use of private media offerings, with women choosing private offerings more frequently, also suggests that media preferences are influenced not only by structural factors such as education and age, but also by gender-specific usage patterns, as described in research on differential media appropriation [13]. Overall, these results underscore that media use must be understood as socially differentiated behaviour and that simple linear explanations are insufficient. The observed patterns of news platform use, and video news consumption (see Table IV) reflect well-established forms of differentiated media use along demographic and educational lines. The broad reliance on multiple platforms, alongside distinct subgroups relying exclusively on social media or television, is consistent with research showing that contemporary news consumption is increasingly hybrid, combining legacy and digital media rather than replacing one with the other [14]. At the same time, the continued existence of single-platform users suggests persistent inequalities in access, routines, and media repertoires [15].

B. Attitudes towards AI

Generally, the attitude towards AI in media industries was evaluated as rather positive and rather negative much more than the definitive stances of positive or negative as shown in Tables V-VIII with later waves recording a slight change in attitudes towards a more negative view generally. Another interesting finding are gender differences within the results for attitudes towards AI and news habits as presented in Table VI or creator identification in Figures 11-12. Even with all three waves featuring a slightly higher number of female participants, a tangible difference can be found with women being more critical of AI but also voting for a human creator more often while men are shown more open towards AI technologies also voting towards a human creator more often. Interestingly in education levels, entry level and higher level often mirror each other's attitudes when it comes to AI in media with a slightly more critical view than medium level education participants as shown in Table VII. Table VIII displays attitudes within age groups showing a rather negative attitude towards AI technologies within people aged 61 and older. This pattern may reflect generational differences in media technology familiarity, as discussed in prior research (ref. [16]).

C. Experiences in Video Editing and AI-use in Media

One of the most prominent findings is that of recipients who have some or a lot of experience in video editing voting in favour of clearly flagged AI content in media instead of having to guess whether AI was utilised in the creation process of anything as shown in Figure 1. Another statement that received high agreement is the worry of news factuality when AI replaces human workforces highlighting the importance of employing human experts to verify AI products when it comes to consumer trust. Taken together, the findings in Figures 2 and Table IX point to a broader ambivalence toward AI in media production. Such ambivalence has been widely documented in research on automation and algorithmic systems, where users simultaneously recognise functional benefits while expressing normative and trust-related concerns ([17]; [18]). The comparatively low agreement with the call for greater AI use is consistent with recent evidence of technology fatigue and growing scepticism toward pervasive automation in everyday media environments [19].

Participants' evaluations of statements comparing AI tools with human expertise further underscore this ambivalence. Responses indicate uncertainty regarding whether AI can achieve results comparable to or better than those of human editors, while also revealing that users care about the origin of media content, suggesting a lack of neutrality toward AI-produced material. This aligns with prior research showing that audiences often judge algorithmic systems not only on performance but also on symbolic and professional expectations associated with journalism ([20]; [21]).

When asked directly about preferences for human versus AI-based video news editing, participants expressed a clear, albeit moderate, preference for human editing without fully rejecting AI-assisted approaches. This pattern is consistent with studies on conditional acceptance of automation, which show that audiences are willing to accept algorithmic support when human oversight remains visible and meaningful [21]. Finally, the slight agreement with the statement that AI tools may reduce emotional bias in decision-making reflects the well-documented tendency to attribute objectivity and rationality to automated systems, even in the presence of broader scepticism [22].

D. Video Experiment

A key finding is that average ratings of human-edited and AI-edited clips were descriptively similar across multiple dimensions. Both were ranked much higher than random editing as shown in Figures 3 and 4. When forced to assign a "human-edited" or "AI-edited" label to the different variants, a majority of the participants assigned the label "human-edited" to both AI edited video news clips and human edited video news clips. Surprisingly, the human edited video news clips were assigned the "AI-edited" label too, as shown in Figures 7-9. All results are displayed with 95% confidence intervals for descriptive purposes. In Figures 3 and 4, the average Likert-Score is illustrated for each of the eight judged statements, (compare Table I), alongside the corresponding 95% confidence intervals. Likert-scale means are reported in rounded form for visual clarity, while all analyses were conducted on the original values.

Overall, AI edited, and human edited video news clips delivered similar average scores on the Likert-scale, recording stronger agreement with the statements except for the inconsistency/incorrectness potential (5) whereas the randomly edited video news clips were scored lower in average for most statements. The more content-related statements (see Table I, statement (1)-(3)) are scored highest in average for AI edited and human edited video news clips. Especially the matching of the voiceover to the visual material (1) received highest scores in average, closely followed by the scene selection illustrating the categories of news well (2). Professionality of the edit (3) and resemblance to other news programs (4) also received high scores with AI-edited and human-edited clips showed similar average ratings on these dimensions. Inconsistencies / incorrectness (5) were scored much lower than random and met more disagreement. Memorability (6) was scored lower in average than other aspects with the smallest difference between all three editing variants. The human editing scores were slightly higher in average when it comes to making the video interesting (7), and emotionality (8) was scored low across all three variants. Figures 5 and 6 present the progression of the video experiment employing both KIGVI iteration 1 in wave 1 and KIGVI iteration 2 in wave 3. With different users participating in wave 3 compared to wave 1, values shifted across the whole matrix bringing the human edit and the KIGVI algorithm edit even closer together. Figures 7-9 especially highlight the lack of congruent creator identification of the presented clips with the KIGVI algorithm passing as human more often than as AI and even the human edit receiving the AI level at around 20% across all three sub-waves. Participants' lack of correct identification of AI and human products was already discussed in reference [23] which aligns well with these findings, widening the research area to moving images from the previous text and still image generation. It is noted that Figures 10-12 display voting behaviour without accounting for whether the selected choice (human-edited or AI-edited) corresponds to the actual editor of the video news clips.

In this paper, we report findings from a cross-sectional survey with 2,219 participants across three independent waves, examining audience perceptions of video news clips edited by AI-based systems and by professional human editors. A total of 48 video news clips is **used** in the study, containing three categories of news, four video news clips per category, and four editing variants of each video news clip with three editing variants in wave 2. Two AI editing variants are applied in waves 1 and 3 with one editing variant receiving a second iteration. In addition, two anchor variants are used. The professionally human edited video news clips serve as a high anchor. Randomly edited video news clips serve as a low anchor. The participants were asked to judge eight statements on a Likert-Scale to assess the quality of a video news clip. Across multiple quality dimensions, ratings of AI-edited and human-edited clips were descriptively similar, with overlapping confidence intervals on several indicators. Participants were generally unable to reliably identify whether clips were edited by humans or AI systems. Furthermore, even when scoring AI edited variants lower, an identification as AI does not always happen.

The results indicate that, based on audience perceptions and the applied evaluation criteria in Table I, AI-edited clips were often rated similarly to human-edited clips, without implying equivalence in technical or professional performance. Lower ratings for memorability and emotional engagement across all variants suggest that these dimensions may be less sensitive to differences in editing style within short-form news formats. Additionally, the low scoring random edit could indicate faithful responses, as the random variant videos were lower in quality and included clips that did not fit the categories of news of the overall videos. Seeing this represented in the matrix questions allows to interpret, that users filled out the video experiment portion genuinely paying attention to the videos. When comparing audience evaluations of CLIP- and KIGVI-edited clips, both variants were more frequently classified as human-edited than as AI-edited. Across the statement matrix, KIGVI-edited clips received higher average ratings than CLIP-edited clips on the measured dimensions, although these differences are reported descriptively and do not constitute evidence of algorithmic performance differences. Park, Oh, and Kim [24] already found social media users to be incapable of distinguishing AI and human made content, in their case generative AI created images and Instagram captions. These findings align with our findings of recipients not being able to distinguish the AI from the human edit. Later samples expressed more critical attitudes toward AI tools in media, which may reflect growing scepticism, although this cannot be interpreted as a temporal change.

VI. LIMITATIONS AND OUTLOOK

The presented results offer a closer insight into the attitudes towards AI in media landscapes and give a first view on the performance of the KIGVI algorithm in the previous and the improved iterations. These findings are unique in showcasing reception of algorithmic editing for video news as opposed to the previous research focus on generative AI usage for texts and images only. The presented findings help define guidelines for public and private news companies on how to use AI technologies in editing, offer a first perspective on recipient acceptance of the technologies and showcase that integrating such strategies can result in acceptance but requires transparent flagging of the displayed content. In the interpretation one must keep in mind that all results are mostly based on bivariate analysis and effects from multiple correlations, multicollinearity, and interactions are not considered. With the significant difference in education levels found for wave 2, these drastically different levels impact all findings especially for survey wave 2 highlighting that survey participants were different across all waves. This in turn presents in the data leading to the choice to mostly exclude the data for wave 2 in the results.

Future research will focus on the improvements of the KIGVI algorithm much more in detail while including further methods of analysis including statistical models and a Difference-in-Differences [25] approach. Another angle to consider would be the potential of oversaturation and the possible fatigue of recipients when it comes to AI tools in general.

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